Extended Features using Machine Learning Techniques for Photo Liking Prediction

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Motivation



- number of posted photos increases daily[1]
- hard for user to select or find good photos based on appeal or liking
- how to decide if a photo is good or not for a social media platform?
- is it possible to automatically predict if an image will be liked or not?

→ connection between human rating, aesthetic appeal and liking decisions

[1] for Flickr: average 1.68 million photos per day for 2016, see [fli18]

Human rating, aesthetic appeal and liking

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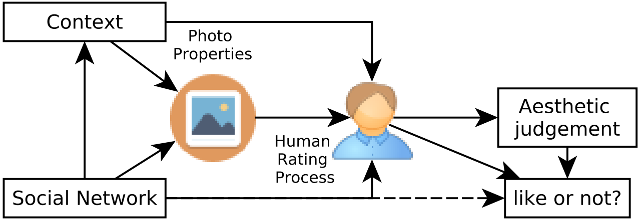


Figure: aesthetic and liking, based on Leder et al. [Led+04]

- aesthetics: artwork, intent of artist, genre of art, perception, . . . [Jos+11]
- main factors for human aesthetics judgment: the photo, the context and the social influences [Led+04]
- lines between aesthetics and liking get blurred [LRB16b; LRB16a]

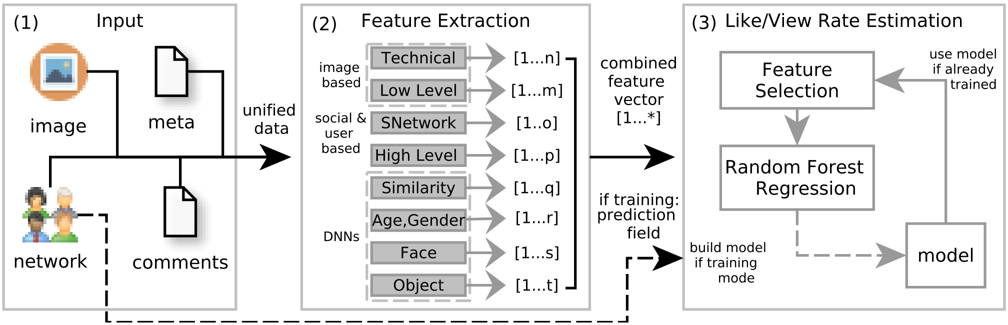
→ features and extensions

State of the art features and extensions

- many other works for photo aesthetic prediction published, e.g. [Dat+06; WBT10; KDH14; Kal+15; Tot+14]
- mostly only focused on classification problem
  - → focus on a regression problem formulation for liking prediction
- or using only low level features [Dat+06; WBT10], or titles and other data [KDH14]
  - → extend and combine feature ideas
  - → image, social network, natural language analysis and deep learning

→ our prediction framework

Our general approach



- features: technical, low-level (LLF), high-level, DNNs, social network (SN)
- focus on $log(\#like)/log(\#view)$ = like/view rate

→ example feature group: DNNs

Example feature group – DNN

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- using several **pre-trained** Deep Neural Networks (DNNs)
- **lastLayerValues**: inception V3 [Sze+15], similar approach for NR video quality [GSR18]
- **hash, hashProbs**: using image similarity DNN for image retrieval [Lin+15]
- **age, gender**: using DNN [RTV15; RTV16] for age and gender estimation
- **faceCount, maxProbFace**: DNN for face detection [PVZ15]

→ dataset for evaluation

Dataset – crawled images from 500px

Crawled 500px images and used samples for experiments.

category / sample	# crawled pictures	$log(\#like)/log(\#view)$ rate r min r	max r	$\bar{r}$	$\sigma(r)$
editors	20975	0.43	0.83	0.68	0.05
fresh	59130	0.10	0.86	0.62	0.11
sample9000	9000	0.10	0.82	0.62	0.11
combined20k	20000	0.11	0.83	0.65	0.09
all80k	80105	0.10	0.86	0.63	0.10

each sample shows similar distribution for $log(\#like)/log(\#view)$ rate

$\rightarrow$ evaluation

Evaluation of Feature Groups

Which feature groups are important? using *sample9000*

- *RMSE* and R^2 for leave-one-out experiment; $* =$ feature set

leave-out	technical	low-level	high-level	SN	DNNs	ALL*	LLF*
RMSE	0.098	0.098	0.098	0.104	0.097	0.098	0.108
R^2	0.233	0.228	0.229	0.135	0.255	0.231	0.072

- social network (SN) features show high impact
- better performance without DNNs (could be sample9000 property)
- single feature: show small impact (extended feature importance analysis)

$\rightarrow$ large scale evaluation

Evaluation of Photo-subject Derivable Features

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Can we just use photo derivable features?

- OPD= technical, LLF, DNN features; ALL, LLF= low level features

RMSE	ALL	OPD	LLF	R^2	ALL	OPD	LLF
sample9000	**0.098***	0.105	0.108		**0.231***	0.128	0.072
combined20k	**0.077***	0.088	0.091		**0.326***	0.114	0.056
all80k	**0.085***	0.096	0.099		**0.329***	0.139	0.091

- ALL performs best for all datasets
- OPD can be used to approximate image liking; better than LLF

$\rightarrow$ conclusion

Conclusion and Future Work

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- introduced a framework for image-liking prediction
  - pure image features; social media, meta information and comments
  - combination of image, social network, natural language analysis and deep learning
- performed evaluation of our new features
  - good results in comparision with only low-level features
  - large impact of social network features
  - still hard to predict liking
- open points, possible extensions:
  - other effects/indicators: temporal, psychological, fashion, art, . . .
  - modern aesthetic datasets

Thank you for your attention

. . . . . . are there any questions?

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Full list of features

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Feature groups, **S**=string, **I**=integer, **F**=float, **M**=multiple, SN=social network, LN=local network, * input dependent

Group	Name	Type	Src	Dim
Technical	cameraType, locationName	S	meta	2
	focalLength, ISOValue, shutterSpeed	I	meta	3
	latitude, longitude, aperture	F	meta	3
	height, width, dateInfos	I	meta	4
Low-Level	globalHue/Sat/Val	F	img	3
	subimageHue/Sat/Val 1...9	MF	img	27
	max/min index of SubImgHue/Sat/Val	MI	img	8
	colorDist, noiseDiff, edgeRatio	MF	img	*+2
High-Level	titleWordCount, -NonStopWordCount	I	meta	2
	titleWordLenDist	MI	meta	*
	titleTagJaccSim, -TagWordSim, -Sent	F	meta	3
DNNs	classDistScores, lastLayerValues	MF	img	2053
	hash, hashProbs	I	img	49
	age, gender, faceCount, maxProbFace	F	img	4
SN	commentSentiment, -WordLengthDist	MF	com	6+*
	comment, friendCommentRate	MF	com	*+1
	followers/friends/galleries/groups-Count	I	user	3
	userAffection/photos/favorites-Count	I	user	3
	LN-triangleCount/MeanFoFCount	I	user	2
	LN-2hopReachableUsers	I	user	1